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Improved extended Kalman filter for state of charge estimation of battery pack

Saeed Sepasi [a,*], Reza Ghorbani [a], Bor Yann Liaw [b]

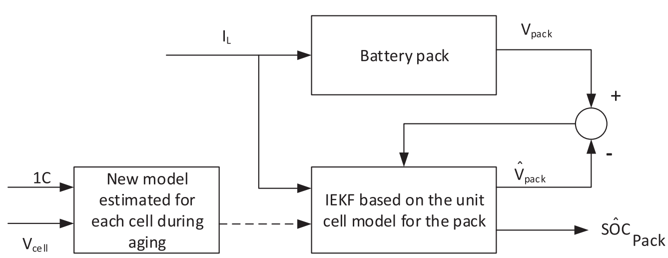
[a] Renewable Energy Design Laboratory, Department of Mechanical Engineering, University of Hawaii at Manoa, 2540 Dole St. – Holmes Hall 347, Honolulu, HI 96822, USA

[b] Electrochemical Power Systems Laboratory, Hawaii Natural Energy Institute, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, 1680 East-West Road, POST 109, Honolulu, HI 96822, USA

HIGHLIGHTS

- Use of a simple optimization algorithm for filtering cells and updating electrical model of aged cells.
- Adapting Kalman gain effect on state estimation.
- SOC estimation for battery pack using improved extended Kalman filter.
- Validation of the proposed method under different current profiles.

GRAPHICAL ABSTRACT



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ABSTRACT

It is difficult to model the behavior of the battery pack accurately due to the electrochemical characteristics variations among cells of a battery pack. As a result, accurate state-of-charge (SOC) and state-of-health (SOH) estimation for the battery pack is a case provocation. The estimation process poses more challenges after substantial battery aging. This paper tries to estimate the SOC of a Li-ion battery pack for an electrical vehicle using improved extended Kalman filter (IEKF) which benefits from considering aging phenomenon in the electrical model of cells. In order to assemble a battery pack, we find cells with similar electrochemical characteristics. Model adaptive algorithm is applied on the corresponding cells of a string to minimize cell-to-cell variation's effect. During the operation, the values of electrical model of each cell are updated by the same algorithm to compensate aging effects on SOC estimation error. The mean value of updated cell's model is used for a single unit cell model of the pack used at IEKF to achieve more accurate SOC estimation. The algorithm's fast response and low computational burden, makes on-board estimation practical. The experimental results reveal that the proposed approach's SOC and voltage estimation errors do not exceed 1.5%.

1. Introduction

Large-scale energy storage consisting rechargeable batteries, have become one of the most popular candidates for electrical energy storage for several reasons. Matching supply and demand in power grids, providing fast response to energy demand, ease for siting and their high energy efficiency are some to name. Under the global demand for reduction in greenhouse gas emissions in the power sector as well as car industry and emergence of renewable energy sources, advanced battery systems are proposed for wide range of applications varying from electrical vehicles (EVs) and hybrid electrical vehicles (HEVs) all the way up to smart grids. Nowadays, Li-ion batteries have become the preferred choice in the field of power battery research and EVs applications. They have gained this popularity as a research topic in industry and academia

* Corresponding author. Tel.: +1 808 956 0767; fax: +1 808 956 2373.
E-mail addresses: saeedsahand@yahoo.com, Sepasi@hawaii.edu (S. Sepasi).

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because of the characteristics of high energy density, less weight, longer cycle life and no memory effect [1]. Storage systems for EVs/HEVs applications to attain their voltage and traction power requirements include tens to hundreds of Li-ion single cells connected in series and parallel or series/parallel. Moreover, to have a secured and safe energy source and distribute power in EVs/HEVs a battery management system (BMS) needs to have an accurate inline estimation of SOC and SOH for Li-ion cells in the battery pack [2]. An appropriate battery model is necessary for proper design and operation of battery systems using BMS. This battery model also helps facilitating estimation schemes stated above [3]. Several modeling approaches are available: empirical models, statistical models, and circuit models [4–8]. Since applications covered in this paper are related to EVs/HEVs and smart grid, an electrical model is preferable [9]. There are numerous models proposed in the literature which are accurate enough for showing the electrical behavior of Li-ion batteries [9–12]. Yet, these models rely on internal parameters of the battery such as the SOC, which is hard to measure [13]. Accurate estimation of SOC under any operating condition still remains a challenge. The estimation process even poses more difficulty in the battery pack due to cell-to-cell variations.

In recent years, there has been great effort for improving the accuracy of SOC estimation of single cells and battery packs [14]. In the case of single cells, the coulomb counting method is the most common method used for SOC estimation [15]. However, this method has several drawbacks including sensitivity to the initial SOC value which leads to inaccurate estimation and accumulated error caused by use of integration. There are several new and improved methods which are based on artificial neural networks (ANNs), fuzzy logic, adaptive observers, sliding mode observers, extended Kalman filter (EKF) and unscented Kalman filter (UKF) [13,16–20] or integration of several individual approaches like coulomb counting and EKF [21]. Last estimation methods are improvements to classical Kalman filter (KF) which are suitable for nonlinear systems [18–21]. Among the SOC estimation methods, some are used in BMSs in EVs/HEVs successfully which are based on EKF [18]. However, there are issues regarding accuracy of SOC estimation as a battery pack ages which is discussed here.

Batteries lose a portion of their capacity in the process of aging which also causes changes in the battery model parameters [22,23]. Moreover, it is important to recognize that SOC is a short term characteristic while capacity fade is a long term one. Yet, they have a close correlation with one another. In order to correlate the SOC with capacity fade and changed model parameters, a method for accurate estimation of SOC is required. Therefore, SOC estimation method for precise prediction needs to update its model parameters adaptively during aging. Most recent, a novel algorithm was proposed to update the parameters of a Li-ion cell model using EKF in which highest priority is given to estimate each cell's voltage accurately [24]. An adaptive extended Kalman filter (AEKF) is proposed to estimate the SOC based on cell voltage measurement [25]. However, the algorithm focuses on covariance matching and ignores aging phenomenon in cells. Estimations which are based on unscented Kalman filter (UKF) or sigma point Kalman filter (SPKF) [19,20] are estimating physical model's parameters as well as SOC, however this convergence takes a considerable amount of time to reach its final value.

As the above methods do not consider cell differences, they are not applicable for the battery pack and mostly focus on single cell's SOC and terminal voltage estimation.

In our previous work [26], brute-force search method is used as an optimization algorithm for finding new electrical model for an aged cell used in EKF. Using this method, SOC estimation error is less than 4%. In Refs. [27], the SOC estimation sensitivity to resistors and capacitors for the model in Fig. 1 is investigated. Based on above analysis, it is clear why we choose resistors in voltage response circuit side in the model which is going to be updated. For the vehicular operation, the electrical energy storage system is composed of hundreds of cells connected in series/parallel due to high energy/power demand. In this paper, a string cells in series is considered as a pack. Concerning the battery pack, the charging/discharging capability of weakest cell is the limiting factor in the branch [28]. Therefore, the characteristic of this cell for battery pack is important during operation. That is why BMS needs to be aware of each cell's SOC to avoid overcharging/over discharging. One of the stated methods is screening process of single cells and use of very similar cells for making a pack [29]. However, this method is time consuming and lots of cells would be omitted, while aging process is not considered. In Ref. [30] an estimator for Li-ion batteries is used which estimates SOC for each single cell in a pack of N cells connected in series. The method's computational burden for a pack of cells is heavy and it is impractical to implement it for in-line estimation in a car [31].

This paper deals with design of battery pack which is composed of 120 cells, connected in series, providing a high voltage level. A single unit cell model of a pack is employed in order to find an accurate SOC estimation for both new and aged battery pack. The single unit cell model is found based on the mean values of updated cells' model. For choosing cells with similar electrochemical properties working as a filter, model adapting (MA) method approach introduced in Ref. [26] is used in which filtered cells are connected in series. MA filtering method guarantees cells' similarity in the pack and consequently enables modeling the pack with a single unit cell. Also, the same approach is used to update the single unit cell's model as the battery pack ages. Moreover, the improved extended Kalman filter (IEKF) which improves the prediction

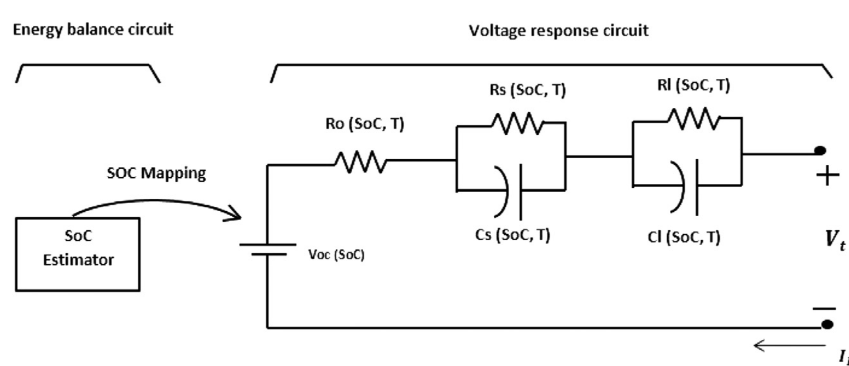

Fig. 1. Schematic diagram of the electrical model based on [5].

accuracy by changing Kalman gain is applied to estimate the battery pack's SOC. The obtained results by FT75 and NEDC reveal that the proposed approach's SOC and voltage estimation error for an aged pack do not exceed 1.5%.

The rest of this paper is organized as follows. Section 2 presents an electrical model used for $LiFePO_4$ cell, which is also used as single unit model for the pack of Li-ion cells in the pack. A review of the EKF is presented in Section 3. Model adaptive approach which is used for filtering cells with similar electrochemical characteristics is discussed in Section 4. In Section 5, cells' model connected in series for battery pack is built based on electrical model. The IEKF-based SOC estimator is proposed for SOC estimation of the battery pack using the single unit cell model. The very next section describes the experimental test applied on battery pack. In this study, a test on a pack of Li-ion cells which contains 120 $LiFePO_4$ cells connected in series is carried out to verify the estimation accuracy of model adaptive-IEKF method for SOC and terminal voltage estimation. The paper concludes with a summery and final remarks.

2. Battery electrical modeling

SOC, as one of the most important information in BMS, is an inner state of each cell [31] which cannot be measured directly during battery operation. As a result, estimating SOC is the only way to obtain its value. To estimate this value, a model for the battery is needed. A variety of battery models are developed to capture Li-ion battery performance for various purposes, among them the equivalent circuit models and the electrochemical models, are widely used in EV studies. The electrical circuit models use equivalent electrical circuits to show I–V characteristics of batteries by using voltage and current sources, capacitors and resistors. Due to the remarkable relaxation effect of the Li-ion battery, the model requirements, including enough accuracy and covering different empirical conditions like working condition of EVs/HEVs, the model presented in Ref. [9] is selected as the battery model-shown in Fig. 1. Energy balance circuit is a part of model which delivers SOC to the voltage response circuit. In this model, the ohmic resistance R_o consists of the bulk resistance and surface layer impedance, accounting for the electric conductivity of the electrolyte, separator and electrodes. The activation polarization is modeled by R_s and C_s, and the concentration polarization is presented by R_l and C_l.

To cover all practical conditions and considering suitable complexity, model's components are assumed to be function of SOC, C-rate and temperature. However, since optimization algorithm used in this paper, inherently has some errors to estimate model parameters with very high accuracy, discharging equations presented in Ref. [9] are neglected. It is assumed that there is just one operating function for charging and discharging.

The electrical behavior of the practical model in Fig. 1 can be expressed as follows:

$$V_t = V_{oc} - V_{trans} - R_o I_L \tag{1}$$

$$V_{trans} = V_s + V_l \tag{2}$$

$$\dot{V}_s = -\frac{1}{R_s C_s} V_s + \frac{1}{C_s} I_L \tag{3}$$

$$\dot{V}_l = -\frac{1}{R_l C_l} V_l + \frac{1}{C_l} I_L \tag{4}$$

where V_t is the battery terminal voltage, V_{OC} is the battery open circuit voltage (OCV) and I_L is load current. V_s and V_l are the short and long time transient voltage responses for charging/discharging respectively.

3. Extended Kalman filter

Kalman filter (KF) is a well-known estimation theory introduced in 1960 [32]. The filter provides a recursive solution through a linear optimal filtering for estimating systems' state variables. However, if the system is nonlinear, a linearization process is undertaken at each step which is used to approximate the nonlinear system with a linear time varying (LTV) system. Using the LTV system in KF, would lead to an extended Kalman filter (EKF) on a real nonlinear system [18]. The calculation process for a nonlinear system including its modeling is given in equations (5) and (6):

$$x_{k+1} = f(x_k, u_k) + w_k \tag{5}$$

$$y_{k+1} = g(x_k, u_k) + v_k \tag{6}$$

where equation (5) represents all of the system dynamics expressed in state equations and equation (6) indicates the output equation of the system with a static relationship. Function $f(x_k,u_k)$ is a nonlinear transition function and $g(x_k,u_k)$ is a nonlinear measurement function. Vectors w_k and v_k denote process and measurement noise which are uncorrelated zero-mean white Gaussian stochastic processes with covariance matrixes Q and R respectively.

At each time step, matrices of $f(x_k,u_k)$ and $g(x_k,u_k)$ are linearized close to the operation point by the first order in Taylor-series and the rest of series are truncated. Assuming that $f(x_k,u_k)$ and $g(x_k,u_k)$ are differentiable at all operating points and $A_k = \partial f/\partial x|_{x=\hat{x}}$, $H_k = \partial g/\partial x|_{x=\hat{x}}$; EKF starts filtering with the best available information on the initial state $(\hat{x}_0^+)$ and error covariance (P_0^+) as shown in equation (7).

$$\hat{x}_0^+ = E[x_0], P_0^+ = E\left[\left(x - \hat{x}_0^+\right)\left(x - \hat{x}_0^+\right)^T\right] \tag{7}$$

An illustration of the EKF is presented in Fig. 2 [33,34].

4. Model adaptive approach for SOC estimation

For the efficient management and control of battery pack, the BMS needs to have accurate estimation of SOC. EKF is an optimum state estimator for nonlinear system which works by recursion. EKF can be used for SOC estimation, since EKF is formed in discrete-time state space, equations (5) and (6) should be transformed into discrete form. Following the form in EKF, the state equations for the nonlinear system of the battery are $x_1 = V_s, x_2 = V_l, x_3 = \text{SOC}$. SOC in contrast to battery's terminal voltage V_t cannot be measured directly. Discrete time state space form for practical model after linearization of equations (5) and (6) are shown in equations (8) and (9).

$$x_{k+1} = A_k x_k + B_k I_{L,k} + w_k \tag{8}$$

$$V_t = y_k = H_k x_k + D_k I_{L,k} + v_k \tag{9}$$

The state vector of practical model consists of three state variables as shown in equation (10).

$$x_k = \begin{bmatrix} V_{s,k} \\ V_{l,k} \\ \text{SOC}_k \end{bmatrix} \tag{10}$$

where SOC_k is the observation of SOC at time step k which is equal to equation (11):

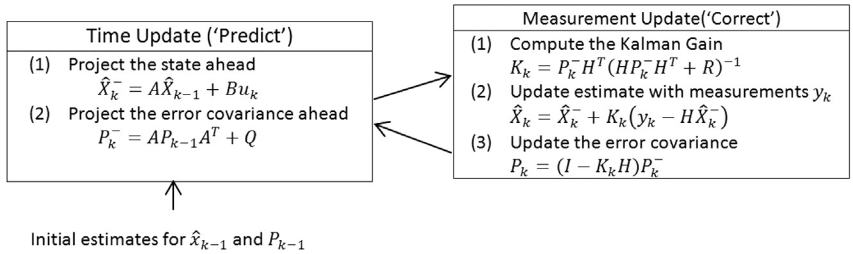

Fig. 2. Complete picture of the operation of the extended Kalman filter.

$$\mathrm{SOC}_k = \mathrm{SOC}_{k-1} + \eta I_{L,k}\Delta t / C_{\mathrm{usable}} \tag{11}$$

where Δt equals to sampling time, is the columbic efficiency and C_{usable} is the battery's available usable capacity. The observation equations of the discrete system are as follows:

$$A_k = \begin{bmatrix} e^{\frac{-\Delta t}{R_{s,k}C_{s,k}}} & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R_{l,k}C_{l,k}}} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$B_k = \begin{bmatrix} R_{s,k}\left(1 - e^{\frac{-\Delta t}{R_{s,k}C_{s,k}}}\right) \\ R_{l,k}\left(1 - e^{\frac{-\Delta t}{R_{l,k}C_{l,k}}}\right) \\ -\eta\, \Delta t / C_{\mathrm{usable}} \end{bmatrix} \tag{12}$$

$$H_k = \left.\frac{\partial V_t}{\partial x}\right|_{x=\widehat{x}_k^-} \begin{bmatrix} -1 & -1 & \left.\frac{\partial V_{oc}}{\partial \mathrm{SOC}}\right|_{\mathrm{SOC}_k^-} \end{bmatrix}$$

$$D_k = \begin{bmatrix} -R_{o,k} \end{bmatrix}$$

4.1. Model adaptive algorithm

The model adaptive-IEKF is a novel approach presented in this paper for battery pack SOC estimation and it is usable for single cells, as well. This approach consists of two parts, model adaptive part and IEKF. As battery ages, estimated SOC by EKF loses its accuracy [27]. For precise SOC estimation of an aged cell, EKF requires an updated electrical battery model. Sensitivity analysis performed in Ref. [27] shows that, R_o, R_s and R_l in voltage response circuit side of the model have the most effect on SOC estimation by the EKF. In other words, as Li-ion cell ages, those parameters must be updated in the battery model. Fig. 3 represents SOC–V_t graph for a new $LiFePO_4$ cell and also the same cell after aging, discharged with constant current (1C in this case). Mean values for electrical elements of the new and degraded cell are presented in Table 1. It is obvious from Fig. 3 that terminal voltage has sharp drops and rises at specific states of SOC. In the case of examined electrochemistry cell, the sudden voltage variations happen at SOC values between 15% and 92% which are considered as reference SOCs here.

Assigning already found two values of SOCs to voltage derivative, the model adaptive approach brings further innovation in the algorithm. The idea is implemented in replacing the obtained new model in EKF with the old model.

According to equation (1), V_t is the open circuit voltage (OCV) of cell deducted by V_{trans} and voltage drop on cell's internal resistance. Since parameters R_o, R_s, C_s, R_l and C_l depend on cell's SOC, V_t is a function of SOC as shown in equation (13).

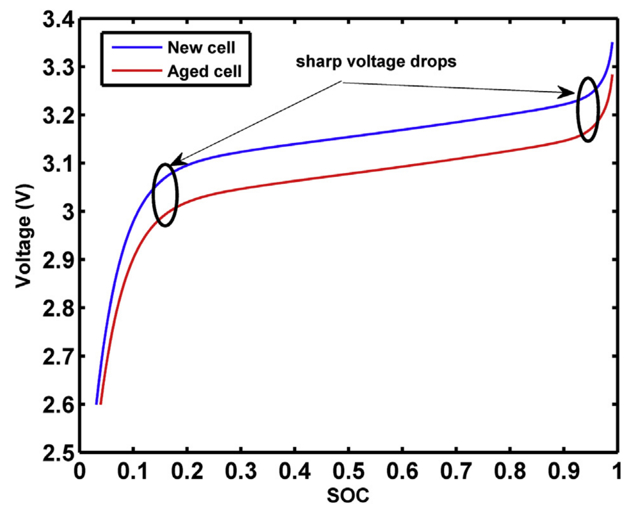

Fig. 3. SOC–V_t graph for a new $LiFePO_4$ cell and the same cell after aging (discharged with 1C).

$$V_t = h(\mathrm{SOC}) \tag{13}$$

Taking derivative of V_t in equation (13) gives:

$$\dot{V}_t = \dot{\mathrm{SOC}} * \dot{h}(\mathrm{SOC}) \tag{14}$$

Knowing that $\dot{\mathrm{SOC}} = -I_L/C_{\mathrm{usable}}$, equation (14) is reduced to:

$$\dot{V}_t = -\frac{I_L}{C_{\mathrm{usable}}} * \dot{h}(\mathrm{SOC}) \tag{15}$$

Graph of -$\dot{V}_t$ for a new cell and an aged cell are shown in Fig. 4. There are two abrupt changes in $\dot{V}_t$ versus SOC graph discharged with a constant current (1C). These two points are assumed reference points in which their SOC can be determined from cell's chemistry. The SOC values for the reference points are set to 92% and 15%.

According to [27], the battery model is sensitive to R_o, R_s and R_l in electrical circuit. In addition, each of the elements are a function of SOC according to the following equations [9]:

$$R_o = b_1\mathrm{SOC}^4 + b_2\mathrm{SOC}^3 + b_3\mathrm{SOC}^2 + b_4\mathrm{SOC} + b_5 \tag{17}$$

$$R_s = c_1 e^{-c_2\mathrm{SOC}} + c_3 \tag{18}$$

$$R_l = g_1 e^{-g_2\mathrm{SOC}} + g_3 + g_4\mathrm{SOC} \tag{19}$$

In equations (17)–(19), b_5, c_3 and g_3 have the most effect on R_o, R_s and R_l values. Assuming all parameters to be constant except for b_5, c_3 and g_3 in the aging process of battery, the variable ones are updated using proposed optimization algorithm.

Table 1
Mean values for electrical model's elements for NEW and the same cell after degradation (degraded cell).

	R_o (Ω)	R_s (Ω)	C_s (F)	R_l (Ω)	C_l (F)
New cell	8.2733e − 002	1.5115e − 002	8.3716e + 002	3.6291e − 002	4.7234e + 003
Degraded cell	1.0515e − 001	2.0230e − 002	8.3716e + 002	4.2902e − 002	4.7234e + 003

Equation (20) is minimized at each reference points by the optimization method:

$$(V_t - V_{oc} - V_{trans} - R_o I_L) \tag{20}$$

Cell's terminal voltage and current are necessary parameters for the optimization problem in equation (20). In this equation, V_t and V_{oc} are associated with the aged cell discharged with 1C. There are three unknown parameters with two known SOCs. This equation is minimized at both 15% and 92% SOC values. In other words, there are three overall unknown parameters in two equations. The objective function in two reference points has plenty of local minima and thus optimization algorithms can easily get trapped. To overcome this problem and for finding new model for aged cell, brute-force approach is used. This algorithm is an enumerating method in which all of the feasible candidate solutions for the objective function are calculated and the minimum/maximum of the whole set is found. For our problem, limitations presented in equation (21) is used in optimization method.

$$\begin{aligned}
&.9R_{o,\text{ initial}} < R_o < 1.8R_{o,\text{ initial}}\\
&.9R_{s,\text{ initial}} < R_s < 2R_{s,\text{ initial}}\\
&.9R_{l,\text{ initial}} < R_l < 2R_{l,\text{ initial}}
\end{aligned} \tag{21}$$

where $R_{o,\text{initial}}$, $R_{s,\text{initial}}$ and $R_{l,\text{initial}}$ are the corresponding values of R_o, R_s and R_l for a brand new cell or the latest values of EKF model. In the optimization algorithm, b_5, c_3 and g_3 parameters are incremented within the assigned range and the objective value is calculated for each set of values. The set in which the mean value of error has the minimum value, is selected for placing in the new model. The C_{usable} parameter is updated while the cell is under load using the method suggested in Ref. [35]. The estimated SOCs obtained from EKF method are used instead of the real SOCs.

Based on the foregoing explanations, this method can be summarized in the following steps:

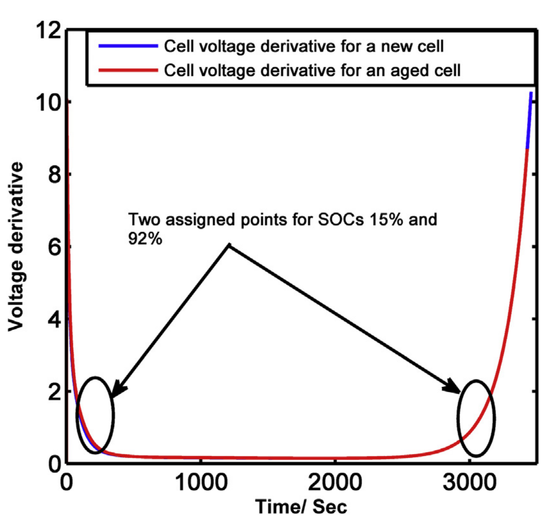

Fig. 4. Voltage derivative for a new cell and an aged cell (discharged with 1C).

1) Discharge the cell with constant current measuring cell's terminal voltage.
2) Calculate derivative of the voltage measured in step one.
3) Assign SOC 92% and 15% as two reference points to voltage derivative.
4) Run optimization algorithm to obtain updated model.
5) Insert updated model to IEKF.

Fig. 5 presents implementation flowchart of the model adaptive IEKF algorithm. It is worthy to mention that similar cells are filtered in the first run. The range of resistor values shown in equation (21) are limited to the following bounds:

$$\begin{aligned}
&.9R_{o,\text{ initial}} < R_o < 1.1R_{o,\text{ initial}}\\
&.9R_{s,\text{ initial}} < R_s < 1.1R_{s,\text{ initial}}\\
&.9R_{l,\text{ initial}} < R_l < 1.1R_{l,\text{ initial}}
\end{aligned} \tag{22}$$

4.2. IEKF approach

In the EKF, the Kalman gain, K_k, represents the relative importance of the error, with respect to prior estimated $\hat{x}_k^-$ equation (23). Basically, the gain controls how much trust is there for the measurements over the estimation.

$$\hat{x}_k = \hat{x}_k^- + K_k(y_k - H\hat{x}_k^-) \tag{23}$$

The EKF doesn't have accurate estimation of states at first steps. The Kalman gain guarantees that measurements are reliable source of updating estimations. After 200–300 steps, when there is almost a good estimation of the states, its value does not alter significantly. Based on these explanations, the IEKF for SOC estimation in EV applications is presented. The linearized system expressed mathematically based on equations (5) and (6) for IEKF is presented in Fig. 6. This figure presents a system with the estimation of the improved extended Kalman filter. In Fig. 6, K_k stands for Kalman gain and blocks containing z^{-1} are single time step delay boxes. For estimating states, the Kalman gain's effect for first 200 steps follows equation (23). In the next steps, since there is a good estimation of Li-ion battery's states, effect of residual is alleviated by reducing Kalman gain's effect on equation (23). It is achieved by raising the Kalman gain to the power of 2.5 as shown in equation (24).

$$\hat{x}_k = \hat{x}_k^- + \left(K_k \hat{\cdot} 2.5\right)(y_k - H\hat{x}_k^-) \tag{24}$$

4.3. SOC definition and estimation of Li-ion cells connected in series pack

As mentioned above, parameters of the new model and each cell's usable capacity can be easily obtained by running optimization for each cell in the pack while discharging the whole pack with a constant current. Using this approach and filtering cells with more than ±10% differences, SOC for the pack is defined as:

$$SOC_{pack} = \frac{\sum_{i=1}^{n_s} C_{usable,i} SOC_i}{\sum_{i=1}^{n_s} C_{usable,i}} \tag{25}$$

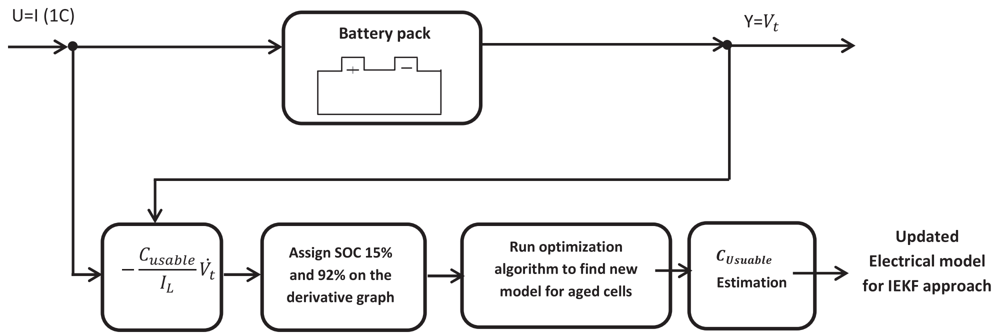

Fig. 5. Implementation flowchart of the model adaptive IEKF algorithm.

where n_s is the number of cells in series and $C_{\text{usable},i}$ and SOC_i denote usable capacity and SOC for the i_{th} cell, respectively. In order to estimate the SOC of the pack defined in equation (25), a single unit cell model for the pack is presented.

The single unit cell model for the pack is similar to the model introduced in Fig. 1 with following equations for the parameters of battery model:

$$R_{o,\text{pack}} = b_1\text{SOC}^4 + b_2\text{SOC}^3 + b_3\text{SOC}^2 + b_4\text{SOC} + \frac{\sum_{i=1}^{n_s}\tilde{b}_{5,i}}{n_s} \quad (26)$$

$$R_{s,\text{pack}} = c_1 e^{-c_2\text{SOC}} + \frac{\sum_{i=1}^{n_s}\tilde{c}_{3,i}}{n_s} \quad (27)$$

$$R_{l,\text{pack}} = g_1 e^{-g_2\text{SOC}} + g_4\text{SOC} + \frac{\sum_{i=1}^{n_s}\tilde{g}_{3,i}}{n_s} \quad (28)$$

$$C_{s,\text{pack}} = \frac{C_s}{n_s} \quad (29)$$

$$C_{l,\text{pack}} = \frac{C_l}{n_s} \quad (30)$$

where n_s is the number of cells in series and $\tilde{b}_{5,i}$, $\tilde{c}_{3,i}$ and $\tilde{g}_{3,i}$ are the identified values for the i_{th} cell of the pack obtained in model adaptive approach as discussed before. About C_s and C_l, since it is assumed that those capacitors are constant and equal for all cells, $C_{s,\text{pack}}$ and $C_{l,\text{pack}}$ are calculated from equations (29) and (30).

IEKF approach is used for SOC estimation of the pack. Since the pack's terminal voltage is measured at each time step, equations (23) and (24) are replaced with equations (31) and (32) respectively.

Equivalently, $\hat{x}_k$ is calculated using the following equation obtained from IEKF:

$$k \le 200 : \hat{x}_k = \hat{x}_k^- + \frac{K_k}{n_s}\left(y_k - n_s H\hat{x}_k^-\right) \quad (31)$$

$$k > 200 : \hat{x}_k = \hat{x}_k^- + \frac{\left(K_k.\hat{2}.5\right)}{n_s}\left(y_k - n_s H\hat{x}_k^-\right) \quad (32)$$

Fig. 7 presents a relation of model estimation for each cell and SOC estimation for the pack.

5. Experimental results

The proposed method is tested in room temperature on a battery pack consisting of 120 $LiFePO_4$ cells, connected in series. These cells are A123 Systems' APR18650m1 $LiFePO_4$ battery with 1.1 Ah nominal capacity. The environment temperature and thus the initial temperature of the cell is assumed to be 25 °C.

A new electrical model for each cell is found after applying proposed optimization algorithm on the aged battery pack. Next, SOC is estimated by application of IEKF. The SOC estimation for the

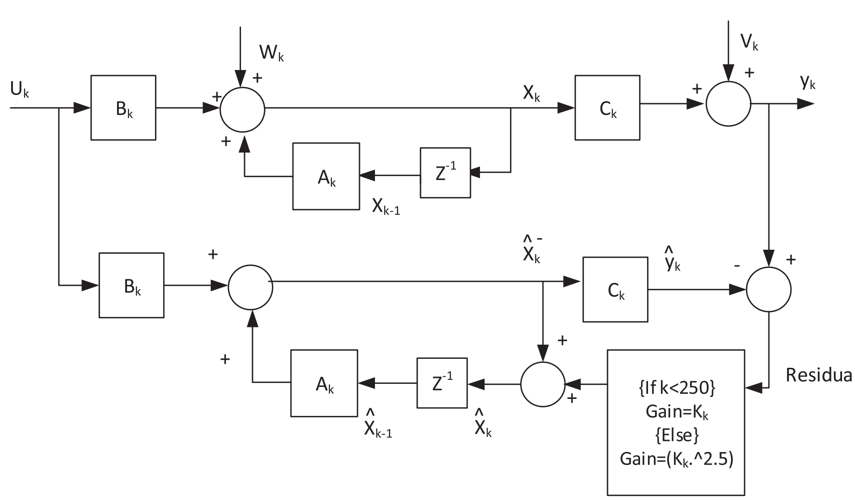

Fig. 6. System with the estimation of the improved extended Kalman filter (IEKF).

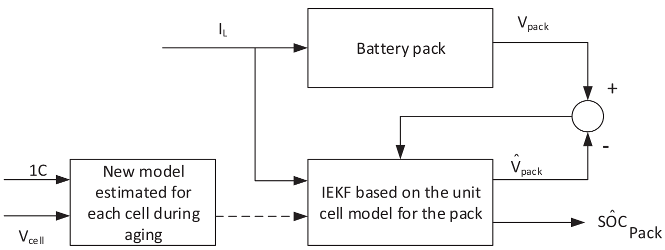

Fig. 7. Relation of model estimation for each cell and SOC estimation for the pack.

battery pack is compared with observed SOC which is based on coulomb counting method.

In the first test, to show advantage of model adaptive-IEKF, the battery pack is charged/discharged with current profile presented in Fig. 8a. Voltage error estimation and SOC error estimation of this approach and model adaptive-EKF presented in Fig. 8b and c, respectively. Model adaptive-EKF benefits from the same approach and equations, except that during the whole test, equation (31) is only used to estimate states instead of applying equations (31) and (32). It is clear that model adaptive-IEKF method is more reliable.

For next test the normalized New European Driving Cycle (NEDC) case study is used to evaluate proposed method. This driving cycle consists of four urban driving profiles followed by another Extra Urban Driving Cycle (EUDC) profile. Based on equation (23), the pack's initial SOC is 96%. The current profile is consecutive without resting time till the pack's estimated SOC reaches 10%. In Fig. 9a the current profile of one simulation cycle is depicted. Fig. 9b shows difference between measured voltage variation for the pack and estimated voltage by model adaptive-IEKF. SOC estimation error is presented in Fig. 9c. In this figure, SOC estimated by model adaptive-IEKF is compared with observed SOC calculated by coulomb counting method. This test stops as soon as estimated SOC for the pack reaches 10%. At the end of experiment, the weakest cell of the pack has 9.8% SOC, which it is still safe and is not considered as over discharged. Mean error of SOC estimation is 0.4%.

For next test, a similar analysis with normalized United States Federal Test Procedure (FTP-75) is designed. FTP-75 is a more realistic driving cycle compared to the NEDC. The FTP-75 is known as a transient driving cycle and represents a driving in an urban environment with frequent stops [36]. Current profile is shown in Fig. 10a. Initial SOC for this test based on equation (23) is 95%. Test is continued with the same current profile till the pack's estimated SOC reaches 10%. Fig. 10b shows voltage estimation error using proposed approach. SOC estimation error obtained from model adaptive-IEKF is depicted in Fig. 10c. When the test is stopped by reaching 10% of estimated SOC for the battery pack, the weakest cell in the branch still has 9% SOC. Mean error of SOC estimation is 1.1%. Based on tests results, it is clear that presented approach has more reliability besides its accuracy. By reliability, we mean that none of the cells in the pack will be over discharged using the presented method in SOC estimation.

6. Discussion and conclusion

In order to have a reliable energy source and distributing power in EVs/HEVs, a battery management system needs to have an accurate inline estimation of SOC for Li-ion cells in the battery pack. EKF is an accurate method for estimating SOC for Li-ion batteries. This estimation is accurate while the model predicts the cells' behavior properly. As battery pack ages, the model cannot predict the battery pack's output accurately and EKF's estimation will not be reliable any more. To overcome this drawback and improve the accuracy and reliability of EKF estimation, a novel method for updating the battery pack's model is proposed. The method used for packs' SOC estimation is called model adaptive-IEKF. This method is an inline and on-board method for updating electrical model for a Li-ion battery pack. Based on experimental results, the concluding remarks can be made below:

(1) This approach uses an equivalent electrical battery model for describing the electrical behavior of a single Li-ion cell. The model describes the dynamic characteristics of the cell consisting one resistor and two RC branches and a voltage source related with SOC, all connected in series. The same equivalent electrical model is used to make a single unit cell model which describes the battery pack's electrical behavior.
(2) Brute-force search method is used as an optimization algorithm for finding electrical model for each new cell in the battery pack. The same method is employed for finding new model of pack's cells in the aging process. Mean values of identified parameters of all cells in the pack are used to make a single unit cell model for the pack. This model decreases computational burden significantly.
(3) An IEKF based algorithm for SOC estimation using single unit cell model is presented to estimate SOC for the Li-ion battery

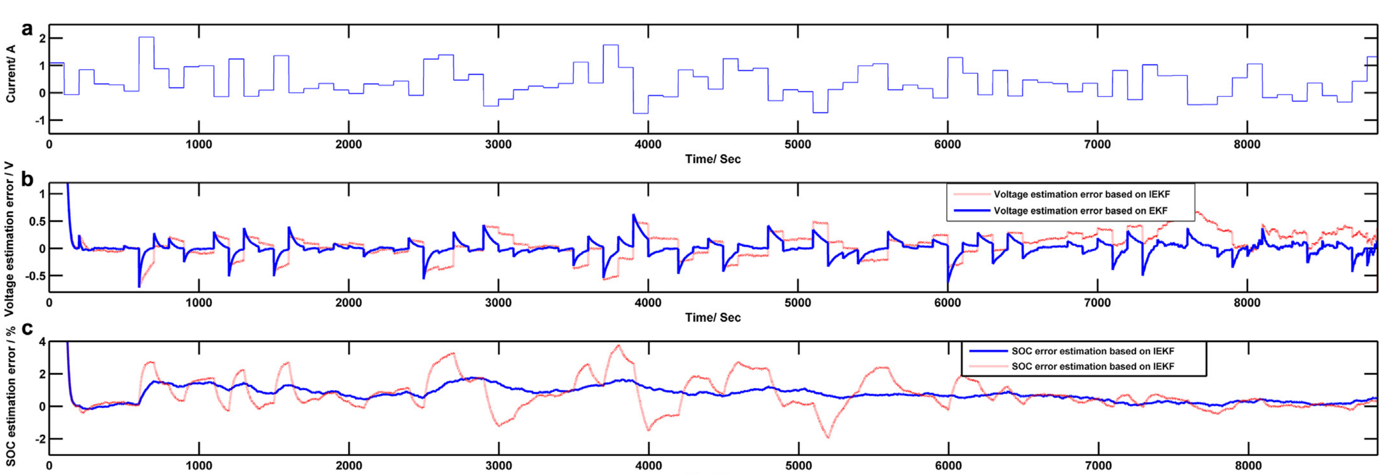

Fig. 8. a. Current profile for first test. b. Voltage estimation error based on EKF and IEKF discharged with current profile presented in Fig. 8a. c. SOC estimation error based on EKF and IEKF discharged with current profile presented in Fig. 8a.

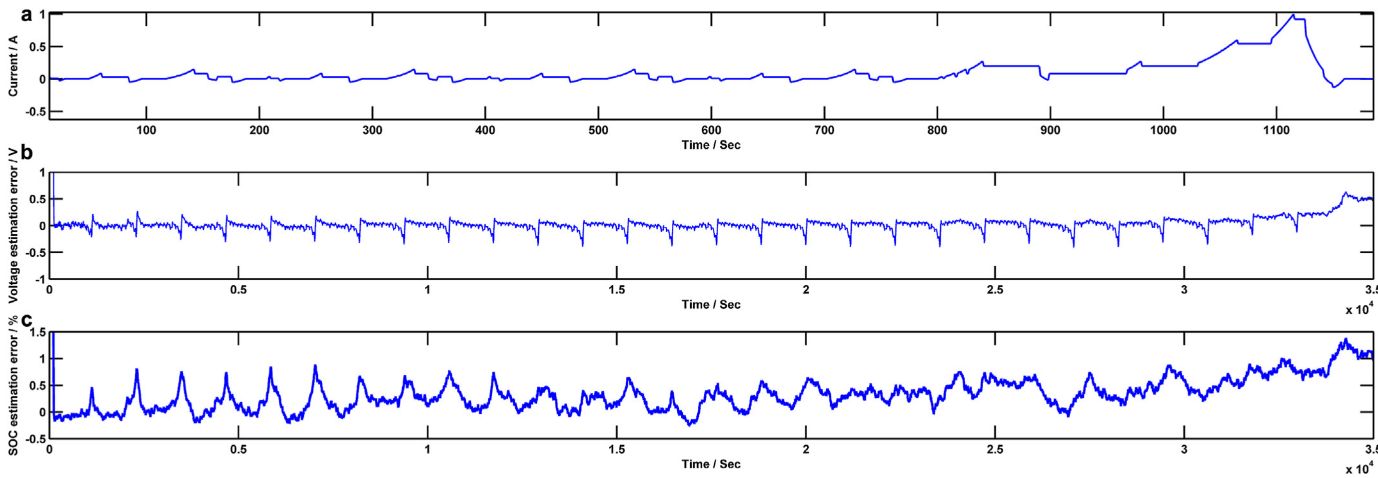

Fig. 9. a. Normalized NEDC current profile. b. Voltage estimation error based on IEKF discharged with Fig. 9a current profile. c. SOC estimation error based on IEKF discharged with Fig. 9a current profile.

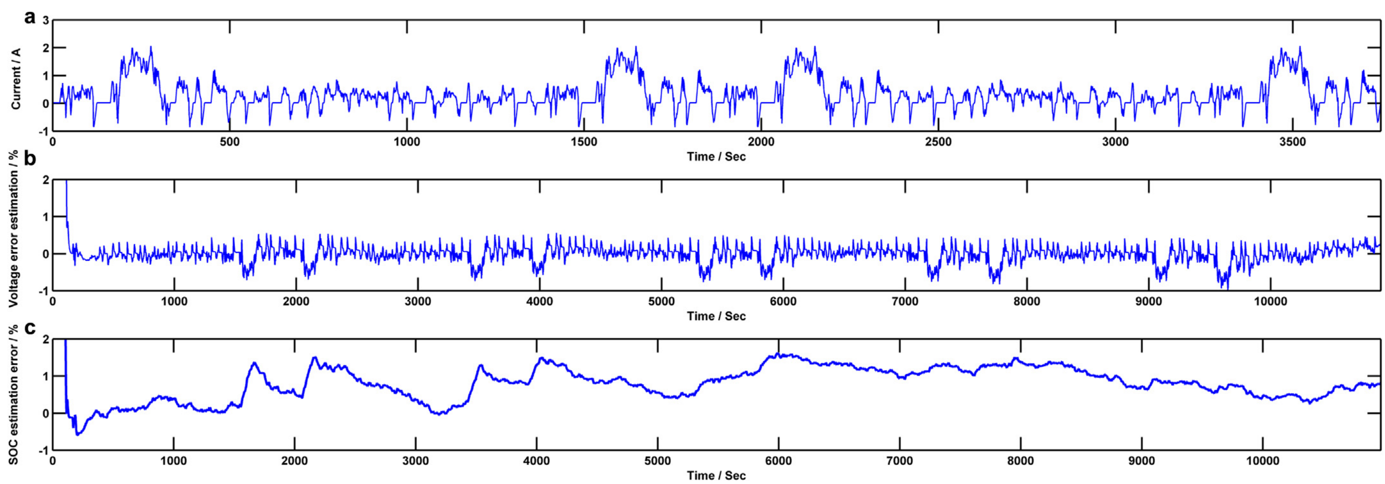

Fig. 10. a. Normalized FTP-75 current profile. b. Voltage estimation error based on IEKF discharged Fig. 10a current profile. c. SOC estimation error based on IEKF discharged Fig. 10a current profile.

pack accurately. This estimator can predict SOC and terminal voltage for Li-ion battery pack.

(4) A Li-ion battery pack with 120 cells connected in series is tested under normalized current profile of FTP-75 and NEDC. Experimental results provide the pack's SOC and terminal voltage error less than 1.5%, which presents robustness and reliability of the proposed approach.

(5) In presented method, as each cell's impedance and usable capacity in the battery pack is estimated, SOH for each cell can be predicted as well. In sum, this approach can predict SOC and SOH simultaneously.

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References

[1] M. Dubarry, B.Y. Liaw, M.S. Chenb, S.S. Chyanc, K.C. Hanc, W.T. Siec, S.H. Wub, J. Power Sources 196 (2011) 3420–3425.
[2] D. Linden, T. Redyy, Handbook of Batteries, third ed., McGraw-Hill, New York, 2001.
[3] M. Matsuura, IEEE Power. Energy Mag. 26 (2011) 1172–1180.
[4] T. Yamazaki, K. Sakurai, K. Muramoto, in: Proc. IEEE PESC, 1998, pp. 210–214.
[5] O. Caumont, P.L. Moigne, C. Rombaut, X. Muneret, P. Lenain, IEEE Trans. Energy Convers. 15 (2000) 354–360.
[6] T. Yanagihara, A. Kawamura, in: Proc. PCC Nagaoka, 1997, pp. 943–946.
[7] J. Peng, Y. Chen, R. Eberhart, in: Proc. Fifteenth Annu. Battery Conf. Applications and Advances, 2000, pp. 173–177.
[8] B.Y. Liaw, G. Nagasubramanianb, R.G. Jungstc, D.H. Doughtyb, Solid State Ionics 175 (2004) 835–839.
[9] L. Lam, P. Bauer, E. Kelder, in: Telecommun. Energy Conf, (INTELEC), 2011, pp. 1–9.
[10] J. Zhang, S. Ci, H. Sharif, in: Applied Power Electronics Conference and Exposition (APEC), 2010, pp. 672–675.
[11] T. Kim, W. Qiao, IEEE Trans. Energy. Convers. 26 (2011) 1172–1180.
[12] M. Dubarry, B.Y. Liaw, V. Svoboda, R. Hwu, J. Power Sources 175 (2007) 366–372.
[13] A. Salkind, C. Fennie, P. Singh, T. Atwater, D. Reisner, J. Power Sources 80 (1999) 293–300.
[14] M. Dubarry, B.Y. Liaw, N. Vuillaume, J. Power Sources 186 (2009) 500–507.
[15] S. Piller, M. Perrin, A. Jossen, J. Power Sources 96 (2001) 113–120.
[16] S. Grewal, D.A. Grant, in: Telecommut. Energy Conf, 2001, pp. 174–179.
[17] I.S. Kim, IEEE Trans. Power Electron. 26 (2008) 2027–2034.
[18] G.L. Plett, J. Power Sources 134 (2004) 277–292.
[19] J. Li, J.K. Barillas, C. Guenther, M.A. Danzer, J. Power Sources 230 (2013) 244–250.
[20] F. Zhang, G. Liu, L. Fang, in: IEEE ICRA, 2009, pp. 1863–1868.
[21] W. Junping, G. Jingang, D. Lei, Energy Convers. Manage. 50 (2009) 3182–3186.
[22] B.Y. Liaw, M. Dubarry, V. Svoboda, R. Hwu, Electrochem. Solid-State Lett. 9 (2006) A454–A457.

[23] M. Dubarry, B.Y. Liaw, V. Svoboda, R. Hwu, J. Power Sources 174 (2007) 1121–1125.
[24] C. Antaloae, J. Marco, F. Assadian, IEEE Trans. Veh. Technol. 61 (2012) 3881–3892.
[25] R. Xiong, H. He, F. Sun, K. Zhao, IEEE Trans. Veh. Technol. 62 (2013) 108–117.
[26] S. Sepasi, R. Ghorbani, B.Y. Liaw, in: IEEE Trans Electrif Conference and Expo (ITEC), 2013, pp. 1–6.
[27] S. Sepasi, R. Ghorbani, B.Y. Liaw, J. Power Sources 245 (2014) 337–344.
[28] M.A. Roscher, O.S. Bohlen, D.U. Sauer, IEEE Trans. Energy Convers. 26 (2011) 737–743.
[29] J. Kim, J. Shin, C. Chun, B.H. Cho, IEEE Trans. Power Electron. 27 (2012) 411–424.
[30] H. Dai, X. Wei, Z. Sun, J. Wang, W. Gu, Appl. Energy 95 (2012) 227–237.
[31] G. Marangoni, Battery Management System for Li Ion Batteries in Hybrid Electric Vehicles, University of Padova, 2010.
[32] R.E. Kalman, Trans. ASME, J. Basic Eng. 82 (1960) 35–45.
[33] M.S. Grewal, A.P. Andrews, Kalman Filtering: Theory and Practice Using MATLAB, second ed., John Wiley and Sons, New York, 2001.
[34] S. Haykin, Kalman Filtering and Neural Networks, John Wiley and Sons, NewYork, 2001.
[35] M. Einhorn, V. Conte, C. Kral, J. Fleig, in: 2nd IEEE ICSET, Proc, 2010, pp. pp.1–6.
[36] DieselNet, Emission Test Cycles, retrieved 2 August 2011, available at: http://www.dieselnet.com/standards/cycles/.